# A Brain Signal-Based Credibility Assessment Approach

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***Abstract*—Deception detection is important for legal, moral and clinical purposes but still it is harder even for security officers and judges. Therefore an effective,light weight approach is a must.There are several technologies used in deception detection. EEG based deception detection is one such approach. P300 wave is most commonly used in EEG based deception detection which depends on a stimuli. The study provides an alternative approach to deception detection instead of using P300.Twelve subjects were participated to the study and EEG signals were recorded while they were telling truths and lies. The preprocessed EEG data then fed in to feature extraction and machine learning algorithm alone with Common Spatial Patterns (CSP) paradigm to create a model. Logistic regression classifier was used as the machine learning algorithm to classify the eeg signal. The test data were used on the trained model with cross validation. There were significant difference between truth telling and lying signals. The average rate of correctly predicted the class was 76%.**

***Keywords*—EEG CSP Logistic regression deception detection ERP P300**

## I. Introduction

According to Ekman [18], lying is the act of one person intending to mislead another, deliberately, without prior notification of this purpose, and without having been asked by the target. Philosophers have long argued that lying is inappropriate despite a lack of a clear prohibition of lying within such oaths [12]. Telling a white lie may not influence in a large scale on individuals or society but gradually it can become a disaster. The notion of the "little white lie" clearly establishes a hierarchy of deceit that sanctions some to lie in certain situations [12]. However, some researches questioned whether white lies are harmless. For example, Patient lying about symptoms to avoid incarceration. Clinical decisions on such kind of a situation may have significant impact on treatment and on a patient's safety. Yet detecting a deception is much harder even for experienced police officers, judges and other forensic professionals as deception detection is importance in legal, moral and clinical implications. A need of a better lying detection application is a must under this situation.

There are a wide variety of technologies available for deception detection based on questioning techniques along with technology that record physiological functions to ascertain truth and falsehood in response. Control Question Test and (CQT) Guilty Knowledge Test (GKT) are such that questioning techniques for deception detection [6]. The Control Question Test is used to control questions with known answers, to serve as a physiological baseline in order to compare them with questions relevant to a particular incident. The CQT provides greater physiological response for telling truth and a less physiological response for lying. The GKT is a multiple-choice format which provides multiple answers including one correct answer and others are incorrect. Physiological response is recorded when subject reads the answers. The controls are the incorrect alternative answers. The greater physiological response is received to the correct answer. Because of that it determines the subject has knowledge about the particular knowledge. For the deception detection the most common and long used measure is the polygraph. Polygraph measures and records several physiological indices such as blood pressure, pulse, respiration, and skin conductivity while the subject asks and answers a series of questions [16]. The idea behind the use of the polygraph is that deceptive answers will produce physiological responses that can be differentiated from those associated with non-deceptive answers. However efficiency and accuracy of the polygraph is still less [3].

Lately researches of deception detection have been involved with brain activities. Mainly there are two techniques for studying on brain functions. One is functional brain imaging and other is recording of brain potentials. Local brain activity is measured using methods such as Positron Emission Tomography (PET) or functional magnetic resonance imaging (fMRI). The latter technique of recording brain potentials measures event-related changes in the EEG that are known as Event-Related Potentials (ERP). FMRI is rarely used in deception detection. Functional MRI (fMRI) is a functional neuroimaging procedure which uses MRI technology to measures brain activity by detecting changes of the blood flow [10] [13] [11]. FMRI relies on cerebral blood flow and neuronal activation. Blood flow of an area of the brain is increased when that region is in use. Good spatial resolution is the main advantage of the imaging methods and low time resolution is a disadvantage of them. ERP have high time resolution and low spatial resolution. Other than that imagine methods are expensive and time consuming than ERPs. ERPs are recorded from the central nervous system. ERPs are considered to be affected by the recognition of important events, which is more cognitively determined activity than autonomic responses.

Brain Computer Interface(BCI) systems can be categorized as endogenous or exogenous depending on the nature of the input signal. Endogenous BCI systems depend on the user's ability to control their electrophysiological activity. Exogenous BCI systems depend on the electrophysical activity evoked by external stimuli and do not require intensive training. P300(P3) wave is a main characteristic of exogenous systems [2]. The most common wave for deception detection is P300 which is a positive component of the ERP. It peaks 300 ms or more (up to 900ms) after a stimulus. P300 is supposed to be an "endogenous" component in the sense that it depends very much on the processing of the stimulus context and levels of attention and arousal [15]. The P300 has been investigated with "oddball" paradigms. In which a subject detects an occasional "target" stimulus in a regular train of standard stimuli. The P300 wave occurs if the subject is actively engaged in the task of detecting the targets. Its amplitude varies with the improbability of the targets. Its latency varies with the difficulty of discriminating the target stimulus from the standard stimuli [14].

The three categories of widely used P300-based lie-detection methods are Bootstrapped Amplitude Difference (BAD), bootstrapped correlation difference (BCD) and pattern recognition (PR) methods [4] [5]. When comparing with BAD and BCD, PR-based lie detection is a promising approach because more physiological features can be extracted from raw P300. Abootalebi et al. used LDA (linear discrimination analysis) to identify P300 responses and obtained a higher detection rate (86%) than that obtained using BAD- and BCD based methods [5]. Support Vector Machine (SVM) was used for the investigation of P300-based lie detection by Gao et al.[7]. When compared with Fisher Discrimination Analysis (FDA) and Backpropagation Neural Networks (BPNN), SVM classifier has obtained the highest average classification accuracy (91.8%) between P300 responses from the guilty subjects and non-P300 responses from the innocents. Abootalebei and Geo used Guilty Knowledge Test to obtain p300 response from the stimuli. Even though P300 based lie detection shows higher level of accuracy which depends on target stimuli. Target identification is useful specially in crime scenarios but people say lies in many situations which may not involve with a target stimuli.

This study focus on training a model for detecting lies using EEG signals. The basic idea behind this study is to process the thinking period of a human brain when telling a lie. EEG signals were recorded when subject thinks and tells lies so that this model would be applied for any situation when people lie such as clinical and crime purposes. To do that instead of GKT this study uses set of questions that subject should answer. It is not based on multiple choices format since that subject should tell a lie and EEG response was recorded. The study exposes an algorithm to train EEG signals acquired by the EMOTIV and create a classification model to predict the class of an unknown data. In training process the CSP paradigm was used with some signal processing and machine learning algorithms. After training two third from the data set one third of data used to test the predictions. The average missclassification rate of the model for the training data set was approximately 24% in the sense the model provided 76% of accuracy.

The organization of the paper is as follows. Section II is an explanation about the methodology then the Section III is about results and finally the conclusion.

## II. Methodology

### A. Subjects

Nine male subjects and three female subjects, all together twelve subjects were taken for the proposed approach. All subjects were in a good condition and no one has had subjected to neurological disorders also they were in good vision. They were generally undergraduate students, or employees of the university.

### B. Data acquisition

As shown in the Figure 1 there are three main parts consists in the central nervous system (also called the brain ). Those are cerebellum, cerebrum and brainstem [8].

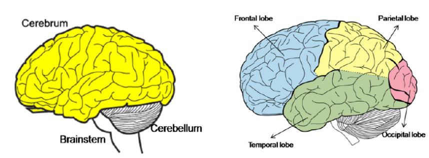


Figure 1: Cortical Area of the Brain

The first part is cerebellum which is the largest part of brain positioned behind the brain stem and below the cerebral cortex or cerebrum. It has two hemispheres like cerebrum. cerebellum is also known as "little brain" which receives the information from nerves, ear, and eyes and organizes this complex brain information. The main functions of cerebellum include the coordination and control of muscle movements, thus responsible for maintaining balance and equilibrium.

The second part of the brain is cerebrum, the largest part of the brain has been divided into two hemispheres those are left and right hemisphere. The outer layer of cerebrum is called cerebral cortex which is consists of an array of neurons and inner layer. The cerebrum is divided into four lobes. Those are Temporal, Occipital, Parietal and Frontal Lobes. The function of each lobe is described in Table5.

Table I: Functions of Brain Lobes

| Lobe | Functions |
|---|---|
| Occipital | Vision<br>e.g. Object and Pattern Recognition |
| Parietal | Somatosensory information<br>e.g. kinesthesis and body awareness, Association and Attention, orientation, recognition, stimuli |
| Frontal | Higher order functions<br>e.g. Memory and Emotions, planning, thinking , worrying, reasoning, planning, emotions, speech, and movements |
| Temporal | Speech center/ Auditory processing center, memory, speech, auditory stimuli, and perception and recognition |

The third part is brainstem which is the lower region that forms the base of the brain. The main functions of brainstem are to Control the blood pressure and circulation, breathing, digestion, heart rate, sleep etc. Following tableI shows the functions of each part of the brain.

For this study EEG data were recorded in a calm, silence and comfortable environment with normal luminosity. Emotiv EPOC, portable EEG headset which has 14 wet electrodes and two references was used for the data acquisition where the channels are placed on scalp as 'AF3', 'F7', 'F3', 'FC5', 'T7', 'P7', 'O1', 'O2', 'P8', 'T8', 'FC6', 'F4', 'F8' and 'AF4'.The electrode locations of the Emotive EPOC+ device can be found Figure 2. This device has wireless connectivity and provides gyroscope data to identify head movements besides EEG data. The emotive control panel software has some functionality such as capability of adding markers while recording, indication of signal strength, pause function, etc. The device was precisely calibrated and tested before the experiment.
Brain electrical activities were amplified and digitized at a rate of 128 samples per second. Digitized data were subsequently analyzed offline using MATLAB software.

### C. Procedure

All subjects answered to simple nine questions twice which were based on their personal information. subjects were asked to sit in front of a computer and questions were provided using a slide show. First they provided wrong answers and second time they provided true answers. A single trail consists with three sections. 15 seconds neutralizing period,relaxation music was played at the beginning to neutralizing the subject. Next, a question was displayed on a slide with a letter of 'F' or 'T' at a corner around 3 seconds. 'F' is for provide wrong answers and 'T' is for provide true answers. In third section a black screen was displayed over 7 seconds in this period

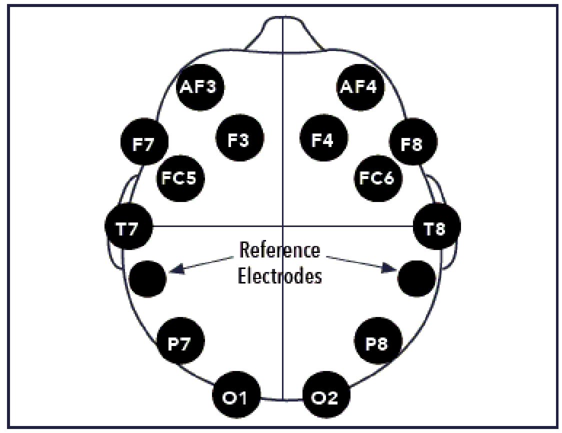


Figure 2: Electrodes

the subject were asked to think and provide the truth or false. Eighteen trials were captured according to above process and EEG signals were recorded for each subject. All together 216 trails were recorded according the above process.

### D. Data Analysis

MATLAB developing platform was used to implement the system to demonstrate the above discussed procedure with the help of BCILAB. BCILAB is a MATLAB toolbox and EEGLAB plugin which can be used for the design, prototyping, testing, experimentation with, and evaluation of Brain-Computer Interfaces (BCIs), and other systems in the same computational framework[1]. Truth and False (Lie) of each subject was considered as two classes and marked as 1 and 2 to find a clear separation between them.

### E. CSP(Common Spatial Patterns)

The CSP paradigm was used for this investigation[1], [9]. The CSP paradigm is based on the design of the Berlin Brain-Computer Interface (BBCI) which is mainly controlled by (sensori) motor imagery. The features exploited by the paradigm in its original form are Event-Related Synchronization and Desynchronization localized in the (sensori)motor cortex, but the paradigm is not restricted to these applications. CSP was originally introduced and first applied to EEG.

Due to its simplicity, speed and relative robustness, CSP is the bread-and-butter paradigm for oscillatory processes. CSP uses log-variance features over a single non-adapted frequency range (which may have multiple peaks), and neither temporal structure (variations) in the signal is captured, nor are interactions between frequency bands.

The paradigm contains an adaptive spatial filter, which is computed using the CSP algorithm. The paradigm is implemented as a standard sequence of signal processing (spatial/spectral filtering), feature extraction, and machine learning. The first preprocessing step is frequency filtering, followed by an adaptively learned spatial filter, followed by log-variance feature extraction and finally a (usually simple) machine learning step applied to the log-variance features. The spatial filtering projects the channels of original signal down to a small set of surrogate channels (usually 4-6), where the mapping is optimized such that the variance in these channels is maximally informative to the prediction task. CSP can be applied to independent components to rate their importance or for better artifact robustness. A wide range of classifiers can be used with CSP features.

Details of the CSP algorithm has been described as follows with an example of classifying single trail EEG during truth telling and lying[17]. $X_{TR}$ and $X_L$ denote the preprocessed EEG matrices under two conditions(truth telling and lying) with dimensions $N \times T$, where N is the number of channels and T is the number of samples per channel. The normalized spatial covariance of the EEG can be represented as follows:

$$R_{TR} = \frac{X_{TR}X_{TR}^T}{trace(X_{TR}X_{TR}^T)} \quad R_F = \frac{X_F X_F^T}{trace(X_F X_F^T)} \tag{1}$$

$X^T$ is the transpose of X and trace(A) computes the sum of the diagonal elements of A. The averaged normalized covariance $\overline{R_{TR}}$ + $\overline{R_F}$ are calculated by averaging over all the trials of each group. The composite spatial covariance can be factorized as

$$R = \overline{R_{TR}} + \overline{R_F} = U_0 \Sigma U_0^T \tag{2}$$

where $U_0$ is the matrix of eigenvectors and $\Sigma$ is the diagonal matrix of eigenvalues. The whitening transformation matrix

$$P = \Sigma^{-1/2} U_0^T \tag{3}$$

transforms the average covariance matrices as

$$S_{TR} = P\overline{R_{TR}}P^T \qquad S_F = P\overline{R_F}P^T \tag{4}$$

$S_{TR}$ and $S_F$ share common eigenvectors and the sum of corresponding eigenvectors for two matrices will always be one,

$$S_{TR} = U\Sigma_{TR}U^T \qquad S_F = U\Sigma_F U^T \qquad \Sigma_{TR} + \Sigma_F = I \tag{5}$$

The eigenvectors with the largest eigenvalues for $S_{TR}$ have the smallest eigenvalues for $S_F$ and vice versa. The transformation of whitened EEG onto the eigenvectors corresponding to the largest eigenvalues in $S_{TR}$ and $S_F$ is optimal for separating variance in two signal matrices. The projection matrix W is denoted as

$$W = U^T P \tag{6}$$

with the projection matrix W, the original EEG signal can be transformed into uncorrelated components

$$Z = WX \tag{7}$$

Z can be seen as EEG source components including common and specific components of different tasks. Using the original EEG, X can be reconstructed by

$$X = W^{-1} Z \tag{8}$$

where $W^{-1}$ is the inverse matrix of W. The column of $W^{-1}$ are spatial patterns, which can be considered as EEG source distribution vectors. The first and last column $W^{-1}$ are the most importance spatial filter patterns that explain the largest variance of one task and the smallest variance of the other.

### *F. Model*

The EEG data were analyzed using several procedures, including signal pre-processing, feature extraction, dimensionality reduction, and classification methods are used to classify the two classes truth(1) and lie(2).

Data acquired from 14 channels were then degraded into 4 channels. The Abootalebi et al. shows that the Fz, Cz and Pz are the channels that gives the highest correlation in deception[5]. Those channels are located in Parietal and Frontal lobes in the brain. According to the device used in this study FC5, F3, FC6 and F4 electrodes were selected, which were belongs to frontal lobe and obtained higher accuracy than other combinations of channels.

Then by using CSP paradigm data were compressed and fed to the classification algorithm. In CSP paradigm calculation additional parameters such as the size of epoch window, filter number and, filter length were adjusted to improve the performance. The EEG data were segmented into epoched data sets from 0 s before to 0.8 s after the stimuli onset.

There are several frequency bands with different attributes that help to identify the states of human brain. According to the Table II, human brain emits Theta(4Hz-8Hz) waves as consciousness and Alpha (8Hz - 13 Hz) waves when the brain is in the relaxed state. The Beta (13 Hz - 30 Hz) waves appear when the brain is in active thinking state and active concentration state. Three of above frequency bands were taken into consideration and tested separately.

Table II: Frequency bands and corresponding brain states

| **Identifier** | **Frequency band** | **Brain state** |
|---|---|---|
| Delta | 1 - 4 Hz | Primarily associated with deep(slow) wave sleep. |
| Theta | 4 - 8 Hz | Appear as consciousness slips towards drowsiness. |
| Alpha | 8 - 13 Hz | Usually found over the occipital region. Indicates relaxed awareness without attention. |
| Beta | 13 - 30 Hz | Associated with active thinking and active concentration. |
| Gamma | 30 - 100 Hz | Represents binding of different populations of neurons. |

Then the pattern recognition methods including feature extraction, feature selection and classification were applied on the signals and the detection rates of them were assessed. The default linear discriminant analysis was replaced with the Logistic regression classifier as the classification. Logistic regression is used as it is an appropriate method for binary classification problems (problems with two class values).

The 3- fold cross-validation was performed by dividing collected data set into three parts. In each iteration two parts were used for training and other part was for testing purpose. Missclassification rates were calculated and finally calculated the average missclassification rate.

## III. Results

Missclassification rate of 3- fold cross validation are as 26.2%, 19.9% and 25.8 %. Average miss-classification rate was 23.9% for alpha band so that accuracy was 76.1%.

Further using several paradigms the test was done to confirm that the CSP gives the highest accuracy. The following graph 3 shows that both CSP and source power comodulation (SPoC) gives the highest accuracy when comparing with others. In fact SPoC can be viewed as generalization of CSP from binary label to continous label. But CSP is more simple and adaptive.

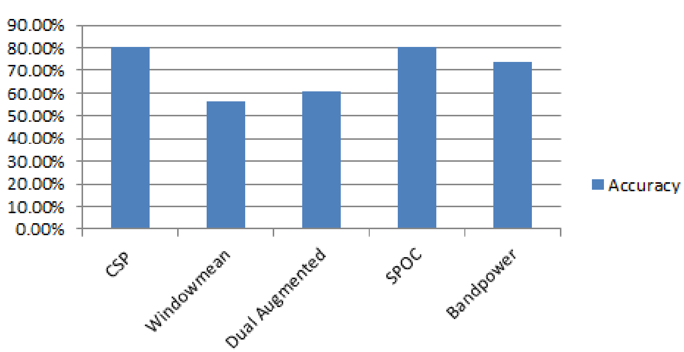


Figure 3: Accuracy Comparison between paradigms

## IV. Conclusion

The device which used in this experiment was barely suitable and easy to use due to wireless access. But still the most accurate data signals were not found due to the shape of the individuals head and the device was not fit with the head of some individuals. The problems with wet electrodes and the loss of concentration also causes with not tracing the appropriate signals. Also some individuals couldn't wear the device comfortably for long time. According to the literature Fz (Frontal), Cz (Central) and Pz(Parietal) are the most appropriate places in deception detection. In this study the electrodes were not placed on those three places basically. The closest electrodes were used which gives a better accuracy than combinations of other electrodes. However if there is a device which can place the electrodes as above and with good resolution, it would increase accuracy. Although the literature used alpha or beta range, the results of this study showed better accuracy for the frequency range of 6Hz-12.5Hz. As the result shown can be concluded that there's a significance difference between the EEG signals of human brain when telling truth and lies. But still there are some miss-classification. But to use this kind of application in legal or clinical implication the accuracy should be in higher level. It can be concluded that overall accuracy is 76%. But the approach can be further extended using different machine learning algorithms as well as using additional features.

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